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Reshaping the structure of the World Trade Network: A pivotal role for China?

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Abstract

In recent years, the global trade landscape has undergone significant changes, particularly in the aftermath of the 2008 financial crisis and more recently as a consequence of Covid-19 pandemic. To understand the structure of international trade and the impact of these changes, this study applies a combination of network analysis and causal inference techniques to the most extensive coverage of available data in terms of time span and spatial extension. The study is conducted in two phases. The first one explores the structure of international trade by providing a comprehensive analysis of the World Trade Network (WTN) from various perspectives, including the identification of key players and clusters of strongly interacting countries. The second phase investigates the impact of the rising role of China on the global structure of the WTN. Overall, the results highlight a structural change in the WTN, testified by a number of network metrics, around the years of the rapid China's growth. Additionally, the reshaping of the WTN is not only accompanied by a significant increase in trade flows between China and its partners, but also by a corresponding decline in trade flows between non-China-partner countries. These results suggest that China played a pivotal role in the restructuring of the WTN in the first decades of this century. The findings of this study have important implications for policymakers and businesses in interpreting the rapidly changing landscape of global trade.

Keywords: world trade; network analysis; causal inference; China's trade

1 Introduction

After decades of sustained and smooth growth, the upward trend in world trade leading to increasing globalization was taken for granted by most countries. Many developing economies – especially in Asia – have experienced a notable increase in imports and exports [1], together with GDP growth rates much higher than the world average. In this context, it was possible to observe a rising role for China, generating an effect sometime named the "China shock" [2], affecting many pre-existing trade patterns. Such a trend has been achieved not only intensively (i.e., through increases in trade flows between countries already trading in the past) but also extensively (i.e., newly created trade relationships) [3]. Since 2008, the path of growth of world trade was put in question by some major perturbations in a relatively short time span: the world recession started by the financial crisis, the trade war between USA and China, the Covid pandemic and most recently the energy crisis following the war in Ukraine.

The 2008 global financial crisis has had far-reaching repercussions on cross-border economic activity, as it had a dramatic impact on economic growth in terms of GDP and decline of trade flow. After a sharp and sudden collapse in international trade in the last quarter of 2008, world trade flows declined by about 12% in 2009 [1]. This exceeded the estimated loss of 5.4% in world GDP [4]. Such a decline in trade flows was unprecedented since World War II, and therefore generated a widespread debate. The contraction in exports was especially acute for small open economies, several of whom saw their trade volumes in the second half of 2008 fall by up to 30% year-on-year. This trade decline contributed to the spread of recessionary pressures even to countries that had little direct exposure to the US subprime mortgage market where the crisis originated. The popular press has provided anecdotal accounts of how manufacturing plants around the world scaled-down production and employment in response to limited export opportunities [5, 6, 7]. As mentioned, this was only the first of a series of turbulences affecting world trade.

During the same time frame, since the end of the past century, the rising of China as a key player in global trade was also observed. Its integration into the world economy brought about a mixture of positive and negative impacts [2]. On the one hand, expanded trade with China opened up new avenues of opportunity for many countries, providing access to a rapidly growing market for their goods and services and thereby driving economic growth and employment. Moreover, the increasing role of China as a leading supplier of manufactured goods and raw materials reduced costs for both consumers and enterprises. On the other hand, China's growing economic activity resulted in increased competition for businesses in other countries, particularly in manufacturing and labor-intensive industries, leading to job losses and closures of businesses, particularly in developed economies. Furthermore, China's large trade surplus with numerous nations elicited concerns about its impact on global trade imbalances, while its lack of transparency and adherence to international trade regulations prompted criticism and caused tensions with other countries [8].

Given the above facts, a relevant question is whether the observed changes in world trade are the consequence of random events or if some structural change occurred in the world trading system. In particular, some research questions arise: How did these patterns changed over time, and what factors influenced these changes? Which countries are the key players in the global marketplace, and what role do they play in shaping trade flows? In order to answer these questions, it is not sufficient to analyze each country in isolation or examine bilateral trade relationships only. As a matter of fact, while bilateral ties are virtual channels of interaction between countries, they can only explain a small fraction of the impact that economic shocks originating in a given country can have on another country, which it is possibly not even a trade partner [9]. A systemic analysis at the global level is needed to fully understand the complexity of the global trade landscape and its structural changes [10].

Our research employs a combination of network analysis [11, 12] and statistical methods to analyze the structure and organization of the World Trade Network (WTN). The application of Social Network Analysis to international trade data has a long history in economic sociology and political science [13, 14, 15], but only relatively recently network analysis has been used to investigate the international trade network quantitatively. Studies have shown that the trade network has become increasingly dense and integrated over time. Links are distributed almost homogeneously among countries, i.e., the network does not exhibit the scale-free degree distribution typically found in a number of real-world networks. However, in terms of intensity (i.e., countries' strength) the distribution is strongly skewed, with a small group of key players forming a well-connected core [16, 17, 18, 19, 20, 21, 22, 23, 24].

To deeply investigate the structural changes in the WTN we focus on the evolving role of China, as the evidence suggests that the rising centrality of this country affected the overall WTN. In our study we complement network analysis with causal inference, a statistical method that aims at identifying the causal relationship between variables while taking into account the potential confounding factors [25]. The goal is understanding how changes in one variable, such as a country's trade policies, affect other variables, such as trade flows or economic growth of other countries. While causal inference is in principle a powerful tool, its application can be challenging in practice, as it relies on the assumption that all confounding variables are measured. In the case of trade with China, the complexity of the global economy, the variety of industries and trade flows, and the political and geopolitical factors that are also at play, can make it challenging to isolate the effect of China's rising role in trade with other countries. We try to minimize such difficulties by combining causal inference and network analysis, i.e., by including network metrics of countries among the model covariates, together with many other non-network variables.

In this paper, the starting point is our preliminary study of the WTN presented in [24], whose results are here summarized, where the evolution of a number of network metrics are discussed for the period 1996-2019. In the first part of the present paper, the above analysis is complemented with a study of the evolution in time of the core-periphery structure of the WTN and of the individual role of each country (centrality). The results are instrumental to the second part of the paper, where the role of China is explored in detail with the tools of causal inference and compared to that of USA, with special attention to the impacts of China evolution on the trade flow of other countries.

2 Methodology and data

2.1 Network analysis

In the case of the WTN, nodes correspond to countries and edges model the flows of goods from one country to another. Since the existence of exports from country A to country B does not imply exports from B to A (and, even when exports are bidirectional, their values are in general different), the WTN is modeled as a weighted directed graph, with no self-edges (exports from a country to itself are not considered). If n is the number of countries, the structure of the WTN is described by the $n \times n$ adjacency matrix $A = [A_{ij}]$, with $A_{ij} = 1$ if there is an edge from i to j, and $A_{ij} = 0$ otherwise. The weighted adjacency matrix (or weight matrix) $W = [W_{ij}]$, with $W_{ij} > 0$ if $A_{ij} = 1$, and $W_{ij} = 0$ otherwise, contains the monetary value of the export from i to j.

We construct the WTN using the BACI-CEPII data set built from data directly reported by each country to the United Nations Statistical Division (Comtrade)[1]. Two countries are considered to have a trade connection if there is a link between them in any of the about 5300 commodity sectors, and the total trade value is the

[1] http://www.cepii.fr/CEPII/en/welcome.asp

aggregate of all sector values. The original dataset provides yearly data from 1996 to 2019. For our analysis, we convert them into biennial periods (i.e., 1996-1997, 1998-1999, ..., 2018-2019) by averaging two years accordingly. Using biennial periods halves the analytical burden while preserving the dynamics of world trade [19], and enables to maximize the number of links between countries. To avoid potential bias and make comparisons between periods straightforward, we keep the network size (i.e., the number of countries) constant by discarding those countries for which data is unavailable in any period of the dataset. After such a pre-processing, our sample contains 206 countries in 12 biennial periods.

2.2 Causal inference and treatment effect

Moving from the results of the network analysis of the world trading system, that show some relevant changes overtime, we want to identify the possible causes. Causal inference is a statistical approach to examine the impact of one variable on another. It aims to determine and quantify the causal effect while accounting for potential confounding factors. This is done by comparing the outcomes of similar groups that differ only in exposure to the target variable (in this case, the rising role of China). To study the effect of China's rise on other countries' trade, we use observational data such as trade data from countries with varying levels of trade with China and employ statistical methods to control for other trade-affecting factors like economic growth and exchange rate. In our analysis, we also want to control for some topological characteristics of the WTN, as they can definitely affect trade patterns. Following Rubin's causal model [26, 27], we introduce the key concepts in causal inference, including the *unit* (the dyad (i, j) of countries i and j), the *treatment* (the dyad (i, j) belonging to a set S of countries with strong trade ties to China), and the potential *outcome* (the bilateral trade flow W_{ij} between countries i and j). In our study, we define the set S to include countries that have China as their first, second, or third largest trade partner (in terms of averaged imports and exports). Thus the treatment variable T_{ij} is defined as 1 if either country i or j belong to S. Our focus is on analyzing the impact of being a strong partner of China in 2001 (resp., 2008) on bilateral trade in 2003 (resp., 2010), corresponding to China's entry into the World Trade Organization (WTO) (resp., the financial downturn). The 2-year lag is allowed to ensure that the treatment is measured before the outcome and not simultaneously. The bilateral trade flow is measured as the logarithm of the average of trade flows for each country dyad (again, the average of the flow from i to j, and from j to i).

For comparison, we performed a similar analysis for countries with a significant trade relationship with the United States for the time periods 2001-2003 and 2008-2010. Unlike the analysis for China, in this case the set S of treated units only includes countries that have the US as their first or second largest trade partner. This distinction was made because, during the specified time periods, China was relatively new to international trade and had limited trade relationships. To maintain fairness and ensure an adequate amount of data to have better balanced treatment and control groups in the causal analysis, it was decided to have a more restrictive definition of set S.

The next step of causal inference analysis is matching. Among the many available methods [28], we utilize Inverse Variance Weighting Matching, which is a method of combining multiple studies' estimates of a causal effect, by weighting each study's estimate by its inverse variance, giving higher weight to more precise estimates. This method provides a more accurate overall estimate and is simple to implement. It also allows for combining results of studies with different designs or measurement methods as long as they estimate the same causal effect. In contrast, other methods, e.g., Propensity Score Matching, can only be used for studies with similar design.

In the context of empirical research, the Average Treatment Effect (ATE) is a commonly used statistical measure that quantifies the mean difference in potential outcomes between the treatment group and the control group, averaged over the entire population. In our framework, it is defined as follows:

$$\text{ATE} = \text{E}(W_{ij}|T_{ij} = 1) - \text{E}(W_{ij}|T_{ij} = 0),$$

where W_{ij} represents the trade flow as described previously, T_{ij} represents the treatment status ($T_{ij} = 1$ if the unit receives the treatment and $T_{ij} = 0$ if it does not), and $E()$ denotes expected value.

The Average Treatment Effect is complemented by two additional measures. One is the Average Treatment Effect on Control (ATC), which measures the average difference in expected outcomes among the subset of the population who did not receive the treatment, conditional on the presence or absence of the treatment. In other words, it only focuses on the control group, measuring the difference if they were to receive the treatment. It is defined as:

$$\text{ATC} = \text{E}(W_{ij}|T_{ij} = 0, X_{ij}) - \text{E}(W_{ij}|T_{ij} = 1, X_{ij}),$$

where X_{ij} represents the covariates used in the matching procedure. The second term is clearly not directly observable, but it might be estimated.

Finally, the Average Treatment Effect on the Treated (ATT) measures the effect of the treatment on the subset of the population that received the treatment, compared to what their outcomes would have been if they had not received the treatment. This measure is useful when the treatment is only given to a subset of the population and there may be selection bias that makes the treatment group different from the control group. It is defined as:

$$\text{ATT} = \text{E}(W_{ij}|T_{ij} = 1, X_{ij}) - \text{E}(W_{ij}|T_{ij} = 0, X_{ij}),$$

where X_{ij} represents the covariates used in the matching procedure.

These statistical measures are critical in empirical research as they provide a systematic way of quantifying the effects of a treatment on a population. Unfortunately, we can only observe one of the potential outcomes for each dyad, i.e., either W_{ij} when $T_{ij} = 0$ or W_{ij} when $T_{ij} = 1$, depending on the treatment that is actually received. For each dyad (i, j) we also observe the treatment T_{ij} that was actually received and a set of pre-treatment characteristics, X_{ij}, which include background information B_{ij} and network features C_{ij}. Based on these characteristics, it is possible to estimate the expected non-observed outcome and compute the above measures.

Table 1 List of network and background variables for causal inference

code	label	description
X_0, X_1	C_{Di}, C_{Dj}	degree centrality of countries i, j
X_2, X_3	C_{Pi}, C_{Pj}	PageRank centrality of countries i, j
X_4, X_5	C_{Ti}, C_{Tj}	clustering coefficient of countries i, j
X_6, X_7	C_{C1i}, C_{C1j}	(binary) 1 if country i, j belongs to Community 1
X_8, X_9	C_{C2i}, C_{C2j}	(binary) 1 if country i, j belongs to Community 2
X_{10}, X_{11}	C_{C3i}, C_{C3j}	(binary) 1 if country i, j belongs to Community 3
X_{12}	lgdp	log product of real GDPs of countries i, j
X_{13}	lgdppc	log product of real GDPs per capita of countries i, j
X_{14}	ldist	log of distance of countries i, j
X_{15}	border	(binary) 1 if i, j share a land border
X_{16}	lareap	log product of land areas of i, j
X_{17}	island	number of island nations in the country pair i, j (0, 1, or 2)
X_{18}	landl	number of landlocked nations in the country pair i, j (0, 1, or 2)
X_{19}	comlang	(binary) 1 if i, j share a common language
X_{20}	comcol	(binary) 1 if i, j were ever colonies after 1945 with the same colonizer
X_{21}	curcol	(binary) 1 if i is currently a colony of j or viceversa
X_{22}	colony	(binary) 1 if i ever colonized j or viceversa
X_{23}	custrict	(binary) 1 if i, j share the same currency or belong to a currency union
X_{24}	regional	(binary) 1 if i, j belong to a common Regional Trade Agreement (RTA)

In particular, C_{ij} contains a few measures obtained from network analysis for countries i and j, namely the degree centrality, the PageRank centrality, the local clustering coefficient, and an indicator related to the outcome of community analysis, i.e., which community i and j belong to (all these measures will be discussed in Sec. 3). Instead, B_{ij} contains information on the economic, historical and geographical background of countries i and j, normally used to estimate bilateral trade flows [29]. These include population and real GDP (in constant dollars) sourced from the World Development Indicators[2], as well as data from the Penn World Table Mark 7.1[3] and the IMF's International Financial Statistics[4]. Country-specific variables, such as latitude and longitude, land area, landlocked and island status, physically contiguous neighbors, language, colonizers, and dates of independence, were obtained from the CIA's World Factbook[5]. Information on regional trade agreements was obtained from the World Trade Organization's website[6]. The complete list of background and network covariates is in Table 1.

3 Results

3.1 The World Trade Network: basic metrics

Figure 1 displays the WTN graphs in 1996-1997 and 2018-2019, the two extremes of the time interval under study. A few countries concentrate most of the total trade value in all periods. Indeed, the bottom panel of the same figure shows that the United States (USA), Germany (DEU), and Japan (JPN) were the dominant trading nations in the first four biennial periods, whereas China (CHN) clearly emerges for the remaining periods: it has the eighth position in the total strength ranking in 1996-1997, but it becomes first since 2014-2015 by surpassing the United States.

[2] https://databank.worldbank.org/source/world-development-indicators
[3] https://www.rug.nl/ggdc/productivity/pwt/
[4] https://data.imf.org/?sk=9D6028D4-F14A-464C-A2F2-59B2CD424B85
[5] https://www.cia.gov/the-world-factbook/
[6] https://www.wto.org/

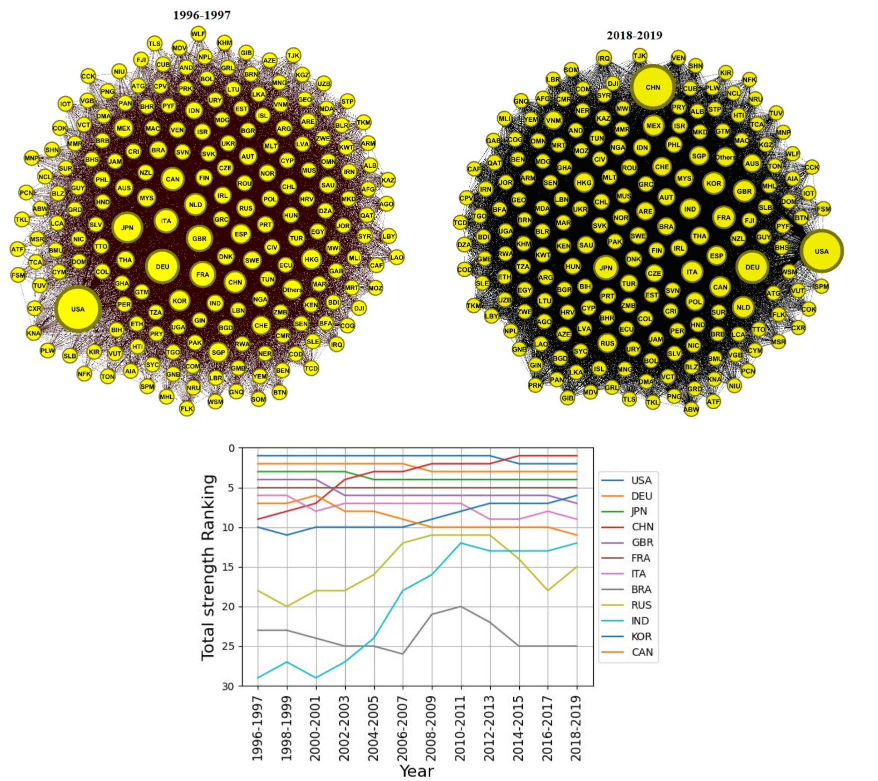

Figure 1 Above: WTN in 1996-1997 and 2018-2019. The size of each node corresponds to the total node strength (import + export) in each biennial period. Below: Ranking position for total strength of a few selected countries.

Figure 2 displays the time evolution of a pool of network metrics for the WTN. Concerning how cohesively countries are connected, the figure shows that density is generally very large, with an average of 0.64 across the entire time span. Our findings agree with the literature about the overall increase (decrease) of density (mean geodesic distance) in 1996-2010, when density increased consistently, but from 2010 to 2019 density changed slightly without a clear trend. Indeed, in the evolution of many topological indicators over time, a change is visible after 2008: for example, density stops increasing, as well as reciprocity, and centralization stops declining. This newly observed generalized change in the trend of topological indicators suggests a possible new evolution of the WTN after 2008, as shown also in [24].

Results in Fig. 2 also show that the relations in the WTN are reciprocal, with more than 8 out of 10 trade relations being bidirectional. From 1996 to 2019, reciprocity increased from 0.85 to 0.88, and this trend matches that of density. Likewise, the WTN is highly clustered with an average value of 0.84. This level of clustering suggests that it is very likely to find transitive relations (i.e., triads) among countries, and this likelihood has increased parallel to the increase in density: as new relations were built over time, new triads of trade partners were developed. This is the result of large trade openness and new bilateral and multilateral trade agreement.

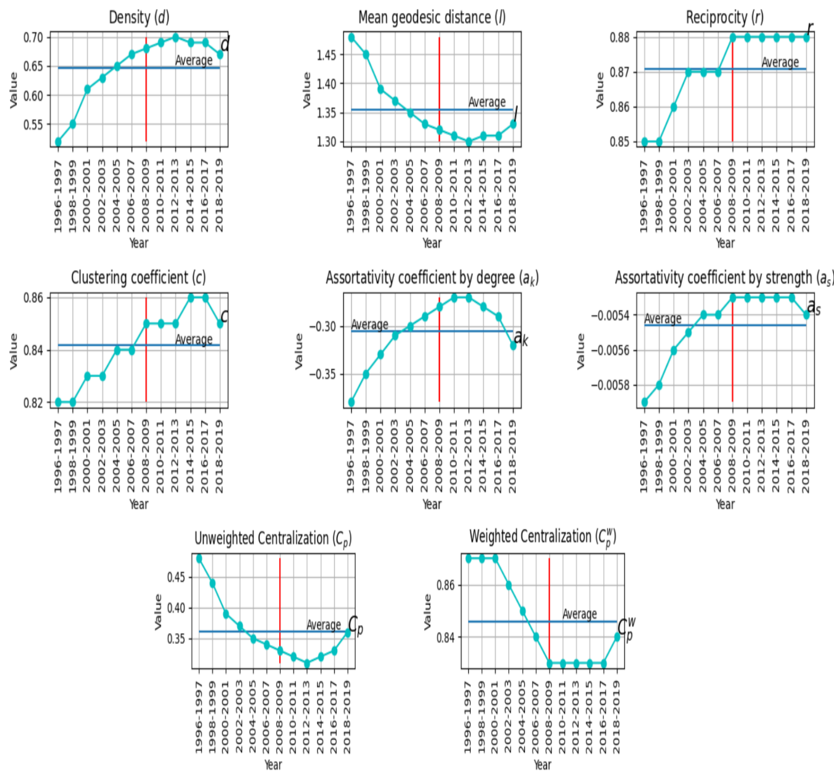

Figure 2 Time patterns of topological metrics of the WTN. The red line marks the 2008 financial crisis.

The evidence of negative assortative mixing by degree (i.e., disassortativity) shows that countries with dissimilar numbers of connections trade with each other. However, their correlations are relatively weak (-0.31 on average) and show an overall decrease in magnitude (from 0.38 to 0.32) towards uncorrelation, which may be due to countries with fewer connections receiving more trade links.

The assortativity mixing coefficient by strength is negative and close to zero. As agreed with existing contributions, there is no clear connective pattern driven by the intensity of countries' strength, which means that countries search for trading partners irrespective of their contribution to the total value of export. Again, it is arguable that the extensive trade margin prevails on the intensive one, as an increase in density drives this result: most countries maintaining a high number of trading partners should break any tendency to establish connections based on the strength of countries. Export diversification aims at increasing the number of trading partners to avoid concentrating trading relationships.

3.2 Core-periphery analysis

The last two panels of Fig. 2 report the time patterns of the unweighted and weighted centralization index, respectively. For these metrics, we rely on the approach introduced by [30] for core-periphery analysis, fully applicable to directed and weighted networks. By elaborating the dynamics of a random walker, a curve

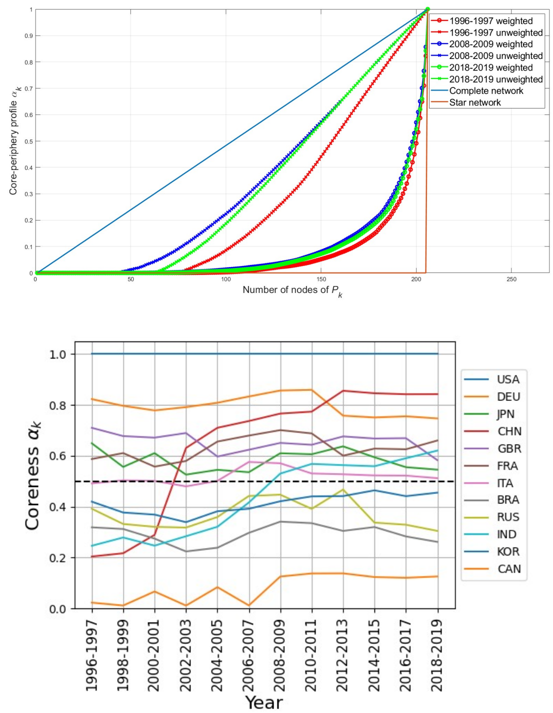

Figure 3 Above: The core-periphery profile of the unweighted and weighted WTN in three biennial periods. The core-periphery profiles of the two extreme cases, i.e., complete (all-to-all) and star network, are also plotted for reference. Below: The time pattern of the coreness c_i for a few selected countries: the core is conventionally formed by countries with $c_i > 0.5$.

(the *core-periphery profile*) and a numerical indicator (the *core-periphery score* C) are derived. This allows one to quantify to what extent the network is centralized or, inversely, organized in a homogeneous structure. Simultaneously, a coreness value $0 \leq c_i \leq 1$ is attributed to each node, qualifying its position and role: nodes with $c_i = 0$ are the most peripheral, while $c_i \to 1$ for nodes at the center of the core.

We refer the reader to [30, 31] for details. Here we only point out that the complete (all-to-all) network and the star network are extreme cases for the core-periphery profile (see Fig. 3). The former has no core-periphery structure as all nodes are equivalent, while the latter is the most centralized network and has $c_i = 0$ for all nodes but the hub, which has $c_i = 1$. Any other network falls somewhere between these extremes: its core-periphery score C is the (normalized) distance of the core-periphery profile from that of the complete network, so that $C = 0$ for the complete (all-to-all) network, and $C = 1$ for the star network: C becomes larger when we consider networks with more pronounced core-periphery structure and stronger centralization.

Figures 2 and 3 show a rather small value of the centralization index, if computed by neglecting weights in WTN and thus only based on the pure topology of connections. Indeed, in a core-periphery network, nodes in the periphery should be minimally connected among themselves [32, 33], and the high density of the WTN is a signal that a core-periphery connective structure is rather unlikely. In sharp contrast, the intensive trade relationship confirms a high centralization if weights

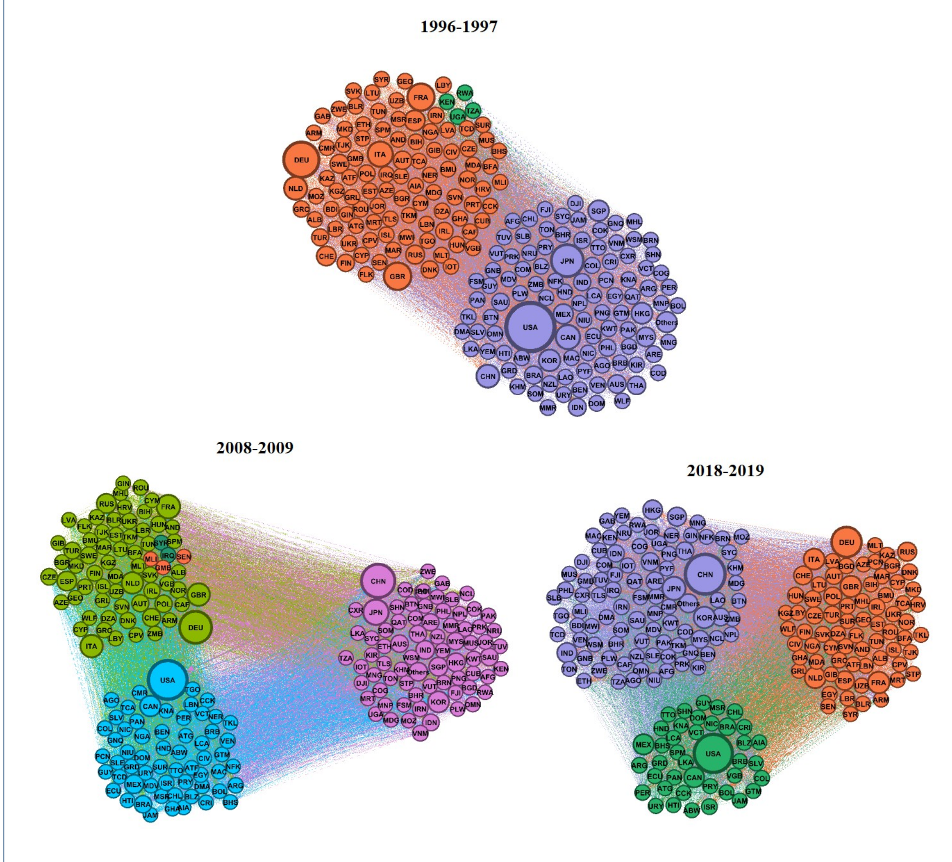

Figure 4 Community structure of the WTN in 1996-1997, 2008-2009, 2018-2019.

are accounted for, with a mean value of 0.84 across the time span. This is consistent with the very uneven strength distribution, which shows that the WTN consists of a small group of countries with extensive trade connections, existing alongside small countries with low trade links connecting each other.

As observed in Fig. 2, the network centralization smoothly decreases until the years 2008-2010, as a consequence of the increasing density due to new forming connections. This trend reverses after 2008-2009: this result is consistent with an increase in the role of emerging economies such as China and India (Fig. 3) entering the core of the network (here the core is conventionally defined as the set of countries with coreness $c_i > 0.5$).

3.3 Community analysis

In this section, we study the possible existence of communities in the WTN to understand the evolution in time of economic integration. We obtain communities via modularity maximization (e.g., [12]) using Louvain method [34], which iteratively optimizes local communities with perturbations to the current partition, until modularity can no longer be improved. The result we obtain is depicted in Fig. 4 for three of the biennial periods analyzed.

In 1996-1997 the network is essentially formed by two communities, the largest one composed by Europe, Middle East and Central Asia, and the other one including

North America, East Asia, and Asian Pacific countries. From 2002-2003 on, with the increasing role of China, the network shifts to a 3-community structure, with modules essentially corresponding to Asia, Europe, and America. In terms of key players, the WTN undergoes a change in fragmentation, across the years, from the two-way partition influenced by the US and Germany, to the three-way organization as a consequence of the rise of China. A large trading partner revision is visible after 2008 for some regions, while, in contrast, the traditional large economies in Europe have remained strongly interconnected, despite experiencing a decline in the number of small countries depending on trade with them. However, although such communities are fully reasonable in geo-economic terms, the low modularity values (around 0.3 in all biennal periods) reveal that the partition is in fact weak, i.e., communities are not strongly separated the ones from the others and have only a moderate prevalence of intra-community trade.

To summarize, the results obtained so far show that the WTN is characterized by an increasing density but not a fully connected structure, with a compact and clustered configuration, and disassortative mixing by degree. The network has homogeneous degree distribution, which differs from most real-world networks (e.g., social networks), implying that scale-free structures are unlikely to describe the WTN. Instead, the inhomogeneous distribution of trade values gives rise to the core-periphery structure of the network, with a concentration of trade in a few countries. However, such a centralization of the network has declined over time as emerging trade nations increased their role. The observed trends in WTN indicators align with the ongoing globalization and integration of international trade, suggesting that the benefits of expanding and diversifying exports may outweigh the costs of establishing new trade relationships. It seems that a high number of linkages in international trade does not necessarily entail an increase in risk exposure, monitoring costs, or resource depletion. Thus, a high level of connectedness may be a desirable and potentially optimal strategy. Nevertheless, these trends have been hindered since 2008, with limited growth in density and no decrease in distance between countries, and a further consolidation of the network's centralization of trade value after 2008.

3.4 Centrality analysis

Community analysis provides useful insights on the global organization of the WTN, but its scope in characterizing the individual role of countries is obviously limited. To gain a more comprehensive understanding of the relative importance of countries in the WTN, other factors, such as the significance of neighboring nodes, the intensity of connections between them, and the distance of connections should be taken into account.

Centrality indicators should be able to assess various aspects of the role of nodes in the WTN. Recent studies [35, 36] have proposed eigenvector centrality as an index for determining the influence of firms or sectors on aggregate outcomes. It is however a measure unsuitable for directed graphs, due to possible degenerations [11] and, to overcome these limitations, we use the PageRank indicator, originally developed for ranking web pages, which can correctly consider factors such as the number of trading partners, their trade value, and the PageRank of trading partners.

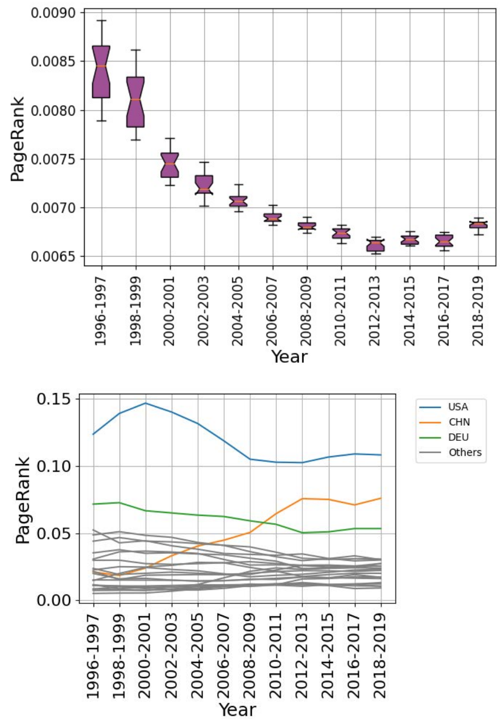

Figure 5 Above: Time evolution of the distribution of the PageRank values for the unweighted WTN (the least significant 10% of countries is not depicted). Below: Time evolution of the PageRank values for the weighted WTN, with USA, China, and Germany in evidence.

We compute both unweighted and weighted PageRank, i.e., on the unweighted and weighted WTN, respectively. The results are summarized in Fig. 5.

PageRank values are normalized, in each biennial period, in such a way that the sum over all countries is 1. Therefore, the decline of highest values and the general homogenization observable in Fig. 5 (top panel, unweighted WTN) testify the trend of globalization, consistent with the already observed rise in WTN density and decrease in the mean distance between countries. Small actors increase their relative importance by acquiring more links and trading partners, while traditional large economies experience a decrease in their pivotal role. Interestingly, this trend slows down after 2008. This change in trend could be related to the effects of the financial crisis, which increased caution in forming new trading relationships, or to the implementation of trade barriers. But it could also be related to the growing role of a new major player.

If the intensity of trade is brought back into the analysis by considering the weighted WTN, Fig. 5 (bottom panel) shows that PageRank values are roughly split into two well separated groups, i.e., high and low values, with the former populated by very few countries, namely only two until approximately 2008-2009 (United States and Germany) and three afterwards, after the rapid rise of China which, in terms of PageRank, starts from the 12th position in 1996-1997 to reach the 2nd place in 2018-2019. To complete the above analysis, we report in Table 2 the lists of top-10 countries in terms of PageRank centrality, for three representative

Table 2 Top countries according to PageRank for the unweighted and weighted WTN

	unweighted WTN			weighted WTN		
rank	**1996-1997**	**2008-2009**	**2018-2019**	**1996-1997**	**2008-2009**	**2018-2019**
1	USA	DEU	GBR	USA	USA	USA
2	DEU	POL	FRA	DEU	DEU	CHN
3	FRA	MEX	POL	JPN	CHN	DEU
4	JPN	DNK	NLD	GBR	FRA	FRA
5	GBR	CZE	USA	FRA	GBR	GBR
6	NLD	AUT	ESP	ITA	JPN	JPN
7	ITA	SVK	DEU	CAN	ITA	NLD
8	AUT	FRA	NZL	NLD	NLD	IND
9	ESP	USA	THA	HKG	CAN	CAN
10	CAN	THA	RUS	ESP	ESP	ITA

biennial periods, and for the unweighted and weighted WTN, separately. It is clearly confirmed that, while small/medium countries may get high ranking in terms of pure connectivity only, large economies have a dominant role when trade values are taken into account.

It should be emphasized that, while China's rise to prominence as the major trading nation is evident from raw data (see Fig. 1), its centrality remains dominated by the United States. This discrepancy can be attributed to China's propensity in dealings with smaller and developing economies, compared to the United States' transactions with are mostly devoted to major economies, including China itself, which have significant centrality. The different role of these two economies, and the impact on their partners, is the subject of the next section.

3.5 Causal inference: The pivotal role of China

Moving from the evidence highlighted in the previous section, attention is now directed towards the impact of China on the pattern of trade flow among nations through an exhaustive evaluation of two key periods, specifically from 2001 to 2003 and from 2008 to 2010. The former period corresponds to the time when China joined the World Trade Organization in 2001, and was therefore able to access world markets with lower barriers, with a lag period of two years to allow the growing influence to take effect. The latter period pertains to the start of the economic recession of 2008, and the two-year lag was applied to enable the burgeoning role to have an impact. For the analysis of the period 2001-2003, a sample size of 6324 units (i.e., dyads of countries) was selected as the control group and 1190 units as the treatment group. The average outcome for the treatment group was 2.508, whereas it was 2.265 for the control group, resulting in a raw difference of 0.243. To account for potential confounding variables, a standardised mean difference (SMD) was calculated, with an SMD value greater than 0.1 suggesting imbalanced proportions between the treatment and control groups.[7]

This study employs a matching estimator approach to address the issue of covariate imbalance. Treatment and control units are paired based on their proximity in terms of confounding variables that are standardized using a weighting matrix, such as the inverse variance matrix. The resulting unit-level treatment effects are averaged to obtain the overall treatment effect. However, the matching procedure may introduce bias due to differences in covariate values, which is addressed using an Ordinary Least Squares (OLS) estimation method.

[7]Results of the pre-treatment statistical analysis are available from the authors upon request.

Table 3 Treatment effect estimate of China and USA (2001-2003)

		st.err.	z	$P > \|z\|$	95% confidence interval	
			China 2001-2003			
ATE	0.388	0.104	3.744	0.000	0.185	0.590
ATC	0.433	0.115	3.770	0.000	0.208	0.658
ATT	0.147	0.113	1.304	0.192	-0.074	0.368
			USA 2001-2003			
ATE	-0.315	0.132	-2.394	0.017	-0.573	-0.057
ATC	-0.321	0.143	-2.254	0.024	-0.601	-0.042
ATT	-0.312	0.170	-1.841	0.066	-0.645	0.020

Table 4 Treatment effect estimate of China and USA (2008-2010)

		st.err.	z	$P > \|z\|$	95% confidence interval	
			China 2008-2010			
ATE	0.154	0.074	2.088	0.037	0.009	0.298
ATC	0.093	0.103	0.907	0.364	-0.108	0.294
ATT	0.222	0.080	2.772	0.006	0.065	0.379
			USA 2008-2010			
ATE	-0.092	0.082	-1.114	0.265	-0.253	0.070
ATC	-0.058	0.087	-0.659	0.510	-0.229	0.114
ATT	-0.117	0.115	-1.013	0.311	-0.343	0.109

The results presented in Table 3 display a positive and statistically significant average treatment effect (ATE) of 0.388 for nations that have China as a major trading partner. This result suggests that China's expanding integration into the global trade network has a pronounced impact on the trade flow among countries, particularly for those nations where China is a substantial trading partner or forming stronger connections with China. The positive effect is confirmed by the Average Treatment Effect in Control (ATC) and Average Treatment Effect in Treated (ATT) measures when focusing separately on the effect of treatment on the control or treated group, respectively. Specifically, for the control group, if they supposedly would have strong connections with China, they may expose a higher trade level compared to when they are not significantly connected to China. A similar argument applies to ATT focusing on the treated group only. This outcome implies that China's expanding integration into the global trade network has a pronounced impact on the trade flows among countries.

To provide a comparative perspective, the same methodology and time frame were applied to the United States and its main partners. The results, as indicated by ATE, ATC, and ATT values in Table 3, suggest that countries that identify the United States as their primary trading partner experienced a marked decrease in trade value in comparison to other nations.

This trend continued during the period 2008-2010 (Table 4), as the 2008 financial crisis originating in the United States hit especially the more advanced economies and much less China. Economies with significant connections to China continued to display higher levels of trade relative to the rest of the world, suggesting that China's growing presence in international trade had a positive impact in fostering trade flows between other nations in the post-2001 period and also played a role in mitigating the negative effects on trade of the 2008 economic downturn.

4 Concluding remarks

In this study, we investigated the structural changes in the World Trade Network (WTN) and the pivotal role of China using data spanning from 1996 to 2019. Our research employed a combination of network analysis and causal inference techniques to gain a comprehensive understanding of the WTN architecture, dynamics, and complex relationships between nations, as well as to quantify China's impact on the network.

Our findings confirmed previous literature in that the WTN is a dense network with a small group of countries having strong trade connections, while many countries have numerous weak trade relations. Our analysis revealed that the network has become increasingly dense, reciprocal, and compact, however, it has not yet reached full connectivity. The WTN exhibits characteristics such as clustering, disassortative mixing by degree, homogeneity by degree, and inhomogeneity by strength, suggesting that it deviates from typical real-world networks. Our network optimization analysis suggested that the benefits of increasing and diversifying exports outweigh the costs of establishing new trade relations. However, since 2008 we observe a slower growth of the network, resulting in a decrease in the number of trade connections, stable distances between countries, and a consolidated concentration of the network. This might be due to the shock generated by the financial crisis.

But after 2008 there were additional changes in the trading system. The WTN displays a weak community structure, with a tendency to become even weaker. Our result reveals that the WTN experienced a significant shift after 2008 when China disrupted the two-group hierarchical organization of world trade, led by the United States and Germany, and emerged as the most prominent cluster in the following period. Furthermore, China continues to appear as the most attractive trade nation as it is receiving more connections. Preferential trading partner revision is visible and geographic re-alignment has become sustained in some regions (Asia-Pacific, South America). In contrast, the traditional large economies in Europe have remained strongly interconnected.

Our study highlights a significant shift in the centrality of countries after 2008. The analysis, based on the PageRank indicator, shows that China joined the United States and Germany as one of the three countries of highest importance in the WTN, while the United States still held a superior position. The findings also emphasize the overall resilience of the position of traditional economies in the WTN: the study suggests that liberalization has led to a denser and more homogeneous WTN, but also indicates that the most intense trade relations remain concentrated among a few countries. The shift in the clustering structure and centrality of the WTN after 2008 presents opportunities for developing economies to enhance the benefits of trade by carefully selecting or revising their trade partners.

Finally, China's increasing integration into the international trade network has had a significant impact on the flow of trade between countries. Specifically, countries with China as a major trading partner tend to have a higher level of trade with each other compared to other countries. This reshaping of the structure of the world trade network has been further amplified by the 2008 financial crisis, which has caused the trade between countries with links to the US to decrease. However, economies with strong connections to China have continued to trade more than the rest of the world. Thus, China's rise in trade has played a pivotal role in promoting trade flows between other countries in the post-2001 period, and played a role in balancing the negative effects of the economic crisis in 2008. Our results indicate that China is not only a major player in the WTN, but also an important hub that connects other countries and reshapes the global trade structure. Overall, this research highlights the important role that China plays in the global trade network and the need for other countries to adapt to this changing landscape.

The policy implications of our research results are noteworthy, providing new insights into the analysis and understanding of world trade at both global and regional levels. Our findings suggest that the liberalization process occurring since the creation of the WTO in 1995 has led to a more dense and homogeneous WTN, although the most intense trade relationships are still concentrated among a few countries. Although the financial crisis left a significant impact on the WTN, the changes in the WTN structure are largely driven by the rapidly growing role of emerging countries, particularly China.

It is essential to acknowledge that the study has certain limitations, including the complexities of factoring in influences such as interference between country dyads and politics/geopolitics, which can hinder a comprehensive examination of China's rising role in trade with other nations. However, the study serves as a solid foundation for further research, including the examination of the impact of the Covid-19 pandemic on the international trade network, an issue that has not been explored due to data availability limitations. Additionally, future studies could delve deeper by examining the trade network at a sectoral level, analyzing the evolution of trade specialization, and investigating the transmission of shocks and the resilience of the network. Additionally, it would be beneficial to consider the tradeable services sector in future research, as it has a strong correlation with products and has become increasingly significant in global trade [37].

Appendix. Summary statistics for causal inference analysis

Table 5 Summary statistics for China (2001-2003)

	Controls $(N_c$=6324)		**Treated** $(N_t$=1190)		
variable	**mean**	**st.dev.**	**mean**	**st.dev.**	**raw-diff**
Y	2.265	3.046	2.508	2.992	0.243
	Controls $(N_c$=6324)		**Treated** $(N_t$=1190)		
variable	**mean**	**st.dev.**	**mean**	**st.dev.**	**SMD**
X0	1.387	0.488	1.259	0.498	-0.259
X1	0.985	0.414	1.037	0.459	0.118
X2	0.016	0.026	0.012	0.021	-0.18
X3	0.003	0.005	0.006	0.008	0.334
X4	0.662	0.156	0.703	0.158	0.263
X5	0.662	0.156	0.703	0.158	0.263
X6	0.238	0.426	0.192	0.394	-0.114
X7	0.186	0.389	0.097	0.296	-0.26
X8	0.251	0.434	0.462	0.499	0.452
X9	0.303	0.460	0.595	0.491	0.614
X10	0.511	0.500	0.346	0.476	-0.337
X11	0.510	0.500	0.308	0.462	-0.420
X12	50.277	2.566	50.604	2.555	0.128
X13	17.958	1.793	17.423	1.769	-0.300
X14	8.036	0.884	8.139	0.738	0.126
X15	0.032	0.176	0.036	0.187	0.022
X16	23.876	3.244	24.709	3.503	0.247
X17	0.318	0.528	0.139	0.347	-0.399
X18	0.309	0.517	0.235	0.470	-0.149
X19	0.189	0.392	0.161	0.367	-0.075
X20	0.091	0.288	0.077	0.267	-0.050
X21	0.000	0.013	0.000	0.000	-0.018
X22	0.018	0.132	0.010	0.100	-0.066
X23	0.016	0.125	0.027	0.162	0.077
X24	0.104	0.305	0.057	0.232	-0.172

Table 6 Summary statistics for USA (2001-2003)

	Controls $(N_c$=2209)		**Treated** $(N_t$=5305)		
variable	**mean**	**st.dev.**	**mean**	**st.dev.**	**raw-diff**
Y	1.818	2.954	2.506	3.051	0.688
	Controls $(N_c$=2209)		**Treated** $(N_t$=5305)		
variable	**mean**	**st.dev.**	**mean**	**st.dev.**	**SMD**
X0	1.266	0.510	1.409	0.478	0.291
X1	0.943	0.371	1.014	0.440	0.173
X2	0.014	0.030	0.016	0.024	0.076
X3	0.002	0.003	0.004	0.007	0.389
X4	0.704	0.166	0.653	0.150	-0.322
X5	0.806	0.115	0.773	0.133	-0.267
X6	0.062	0.241	0.301	0.459	0.653
X7	0.062	0.241	0.301	0.459	0.653
X8	0.197	0.398	0.321	0.467	0.285
X9	0.249	0.433	0.391	0.488	0.308
X10	0.741	0.438	0.378	0.485	-0.785
X11	0.727	0.446	0.375	0.484	-0.755
X12	49.474	2.338	50.685	2.574	0.493
X13	17.696	1.912	17.947	1.746	0.137
X14	7.596	0.85	8.242	0.795	0.785
X15	0.049	0.216	0.026	0.159	-0.121
X16	23.761	2.419	24.111	3.599	0.114
X17	0.117	0.330	0.361	0.550	0.540
X18	0.487	0.620	0.218	0.434	-0.502
X19	0.124	0.330	0.210	0.407	0.230
X20	0.120	0.326	0.076	0.265	-0.150
X21	0.000	0.000	0.000	0.014	0.019
X22	0.005	0.074	0.021	0.144	0.138
X23	0.033	0.178	0.011	0.106	-0.146
X24	0.134	0.341	0.081	0.273	-0.172

Table 7 Summary statistics for China (2008-2010)

	Controls (N_c=4523)		**Treated** (N_t=4012)		
variable	**mean**	**st.dev.**	**mean**	**st.dev.**	**raw-diff**
Y	2.266	3.243	3.15	3.232	0.884
	Controls (N_c=4523)		**Treated** (N_t=4012)		
variable	**mean**	**st.dev.**	**mean**	**st.dev.**	**SMD**
X0	1.456	0.471	1.500	0.462	0.095
X1	1.146	0.430	1.171	0.466	0.057
X2	0.012	0.019	0.013	0.018	0.084
X3	0.004	0.004	0.006	0.010	0.317
X4	0.724	0.139	0.709	0.139	-0.110
X5	0.815	0.116	0.804	0.133	-0.086
X6	0.250	0.433	0.307	0.461	0.127
X7	0.235	0.424	0.231	0.422	-0.009
X8	0.526	0.499	0.258	0.438	-0.571
X9	0.479	0.500	0.231	0.422	-0.536
X10	0.224	0.417	0.435	0.496	0.461
X11	0.287	0.452	0.538	0.499	0.528
X12	50.224	2.392	51.276	2.615	0.420
X13	18.350	1.696	18.007	1.794	-0.197
X14	7.958	0.888	8.275	0.735	0.389
X15	0.029	0.166	0.027	0.163	-0.007
X16	23.181	3.140	24.728	3.258	0.483
X17	0.306	0.518	0.299	0.514	-0.012
X18	0.372	0.551	0.262	0.476	-0.215
X19	0.172	0.378	0.180	0.384	0.019
X20	0.080	0.272	0.092	0.290	0.043
X21	0.000	0.015	0.000	0.000	-0.021
X22	0.019	0.138	0.009	0.093	-0.091
X23	0.031	0.174	0.014	0.117	-0.117
X24	0.286	0.452	0.112	0.315	-0.447

Table 8 Summary statistics for USA (2008-2010)

	Controls (N_c=3517)		**Treated** (N_t=4692)		
variable	**mean**	**st.dev.**	**mean**	**st.dev.**	**raw-diff**
Y	2.716	3.118	2.899	3.226	0.182
	Controls (N_c=3517)		**Treated** (N_t=4692)		
variable	**mean**	**st.dev.**	**mean**	**st.dev.**	**SMD**
X0	1.486	0.478	1.503	0.440	0.039
X1	1.161	0.450	1.182	0.435	0.047
X2	0.013	0.020	0.013	0.018	0.024
X3	0.004	0.005	0.005	0.009	0.216
X4	0.715	0.144	0.709	0.132	-0.043
X5	0.810	0.125	0.804	0.123	-0.05
X6	0.113	0.317	0.383	0.486	0.657
X7	0.105	0.307	0.331	0.471	0.569
X8	0.515	0.500	0.329	0.470	-0.382
X9	0.490	0.500	0.256	0.436	-0.500
X10	0.372	0.483	0.288	0.453	-0.180
X11	0.405	0.491	0.413	0.492	0.017
X12	50.345	2.516	50.918	2.582	0.225
X13	18.035	1.956	18.281	1.648	0.136
X14	7.890	0.853	8.226	0.809	0.405
X15	0.037	0.189	0.024	0.153	-0.076
X16	23.950	3.131	23.942	3.440	-0.002
X17	0.235	0.458	0.344	0.545	0.217
X18	0.408	0.570	0.222	0.443	-0.363
X19	0.123	0.328	0.220	0.414	0.260
X20	0.103	0.304	0.075	0.263	-0.099
X21	0.000	0.000	0.000	0.015	0.021
X22	0.011	0.105	0.018	0.134	0.060
X23	0.028	0.165	0.016	0.125	-0.083
X24	0.213	0.410	0.136	0.343	-0.204

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Abbreviations
GDP: Gross Domestic Product; RTA: Regional Trade Agreement; WTN: World Trade Network

Availability of data and materials
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Authors' contributions
VPH, CP and LT conceived the research, conducted the experiments, wrote and reviewed the manuscript.

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References
1. WTO: World Trade Report 2013 – Factors shaping the future of world trade. Technical report (2013). https://www.wto.org/english/res_e/booksp_e/world_trade_report13_e.pdf
2. Feenstra, R.C., Sasahara, A.: The 'China shock,' exports and U.S. employment: A global input–output analysis. Review of International Economics **26**(5), 1053–1083 (2018)
3. Fagiolo, G.: The international trade network. In: Victor, J.N., Montgomery, A.H., Lubell, M. (eds.) The Oxford Handbook of Political Networks, vol. 1, pp. 669–688. Oxford University Press, Oxford (2017)
4. WTO: World Trade Report 2009 – Trade policy commitments and contingency measures. Technical report (2009). https://www.wto.org/english/res_e/booksp_e/anrep_e/world_trade_report09_e.pdf
5. Levchenko, A., Lewis, L., Tesar, L.: The collapse of international trade during the 2008-2009 crisis: In search of the smoking gun. Technical report, National Bureau of Economic Research, Cambridge, MA (2010). http://www.nber.org/papers/w16006.pdf
6. Shelburne, R.: The global financial crisis and its impact on trade: The world and the European emerging economies. Technical report (2010). https://ideas.repec.org/p/ece/dispap/2010_2.html
7. Chor, D., Manova, K.: Off the cliff and back? Credit conditions and international trade during the global financial crisis. Technical report, National Bureau of Economic Research, Cambridge, MA (2010). http://www.nber.org/papers/w16174.pdf
8. Feenstra, R.C., Wei, S.-J.: China's growing role in world trade. Technical report (2010). https://www.nber.org/books-and-chapters/chinas-growing-role-world-trade
9. Abeysinghe, T., Forbes, K., Abeysinghe, T., Forbes, K.: Trade linkages and output-multiplier effects: a structural VAR approach with a focus on Asia. Review of International Economics **13**(2), 356–375 (2005)
10. Krugman, P.: Growing world trade: Causes and consequences. Brookings Papers on Economic Activity **26**(1), 327–377 (1995)
11. Newman, M.E.J.: Networks: An Introduction. Oxford University Press, Oxford (2010)
12. Barabasi, A.L.: Network Science. Cambridge University Press, Cambridge (2016)
13. Sacks, M.A., Ventresca, M.J., Uzzi, B.: Global institutions and networks: Contingent change in the structure of world trade advantage, 1965-1980. American Behavioral Scientist **44**(10), 1579–1601 (2016)
14. Kim, S., Shin, E.H.: A longitudinal analysis of globalization and regionalization in international trade: A social network approach. Social Forces **81**(2), 445–471 (2002)
15. Mahutga, M.C.: The persistence of structural inequality? A network analysis of international trade, 1965–2000. Social Forces **84**(4), 1863–1889 (2006)
16. Serrano, M.A., Boguna, M.: Topology of the world trade web. Physical Review E **68**(1), 015101 (2003)
17. Kali, R., Reyes, J.: The architecture of globalization: A network approach to international economic integration. Journal of International Business Studies **38**(4), 595–620 (2007)
18. Barigozzi, M., Fagiolo, G., Garlaschelli, D.: The multi-network of international trade: A commodity-specific analysis. Technical report (2009). https://ideas.repec.org/p/ssa/lemwps/2009-09.html
19. Cepeda-López, F., Gamboa-Estrada, F., León, C., Rincón-Castro, H.: The evolution of world trade from 1995 to 2014: A network approach. Journal of International Trade and Economic Development **28**(4), 452–485 (2019)
20. Fagiolo, G., Reyes, J., Schiavo, S.: The evolution of the world trade web: A weighted-network analysis. Journal of Evolutionary Economics **20**(4), 479–514 (2010)
21. De Benedictis, L., Tajoli, L.: The world trade network. World Economy **34**(8), 1417–1454 (2011)
22. Maeng, S.E., Choi, H.W., Lee, J.W.: Complex networks and minimal spanning trees in international trade network. International Journal of Modern Physics: Conference Series **16**, 51–60 (2012)
23. De Benedictis, L., Nenci, S., Santoni, G., Tajoli, L., Vicarelli, C.: Network analysis of world trade using the BACI-CEPII dataset. Technical report (2013). https://econpapers.repec.org/RePEc:cii:cepidt:2013-24
24. Hoang, V.P., Piccardi, C., Tajoli, L.: A network analysis of world trade structural changes (1996–2019). In: Cherifi, H., Mantegna, R.N., Rocha, L.M., Cherifi, C., Micciche, S. (eds.) Complex Networks and Their Applications XI, pp. 490–501. Springer, Cham (2023)
25. Angrist, J.D.: In: Durlauf, S.N., Blume, L.E. (eds.) Treatment Effect, pp. 329–338. Palgrave Macmillan UK, London (2010)
26. Angrist, J.D.: Treatment effect heterogeneity in theory and practice. Economic Journal **114**, 52–83 (2004)

27. Imbens, G.W., Rubin, D.B.: In: Durlauf, S.N., Blume, L.E. (eds.) Rubin Causal Model, pp. 229–241. Palgrave Macmillan UK, London (2010)
28. Imbens, G.W., Rubin, D.B.: Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction. Cambridge University Press, Cambridge (2015)
29. Kabir, M., Salim, R., Al-Mawali, N.: The gravity model and trade flows: Recent developments in econometric modeling and empirical evidence. Economic Analysis and Policy **56**, 60–71 (2017)
30. Della Rossa, F., Dercole, F., Piccardi, C.: Profiling core-periphery network structure by random walkers. Scientific Reports **3**(1), 1–8 (2013)
31. Piccardi, C., Tajoli, L.: Complexity, centralization, and fragility in economic networks. PLOS ONE **13**(11), 1–13 (2018)
32. Craig, B., Von Peter, G.: Interbank tiering and money center banks. Journal of Financial Intermediation **23**(3), 322–347 (2014)
33. Fricke, D., Lux, T.: Core-periphery structure in the overnight money market: Evidence from the e-mid trading platform. Kiel Working Paper 1759 (2012). http://hdl.handle.net/10419/55868
34. Blondel, V.D., Guillaume, J.L., Lambiotte, R., Lefebvre, E.: Fast unfolding of communities in large networks. Journal of Statistical Mechanics: Theory and Experiment **2008**(10), 10008 (2008)
35. Acemoglu, D., Carvalho, V.M., Ozdaglar, A., Tahbaz-Salehi, A.: The network origins of aggregate fluctuations. Econometrica **80**(5), 1977–2016 (2012)
36. Carvalho, V.M.: From micro to macro via production networks. Journal of Economic Perspectives **28**(4), 23–48 (2014)
37. Tajoli, L., Airoldi, F., Piccardi, C.: The network of international trade in services. Applied Network Science **6**(1) (2021)